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ORIGINAL PAPER

Spatial heterogeneity of factors influencing forest fires size in northern Mexico

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Abstract: In Mexico, forest fires are strongly influenced by environmental, topographic, and anthropogenic factors. A government-based database covering the period 2000-2011 was used to analyze the spatial heterogeneity of the factors influencing forest fire size in the state of Durango, Mexico. Ordinary least squares and geographically weighted regression models were fit to identify the main factors as well as their spatial influence on fire size. Results indicate that fire size is greatly affected by distance to roads, distance to towns, precipitation, temperature, and a population gravity index. The geographically weighted model was better than the ordinary least squares model. The improvement of the former is due to the influence of factors that were found to be non-stationary. These results suggest that geographic location determines the influence of a factor on fire size. While the models can be greatly improved with additional information, the study suggests the need to adopt fire management policies to more efficiently reduce the effect of anthropogenic factors. These policies may include more training for landowners who use fire for clearing, closure of roads, application of thinning, prescribed burning, and fire breaks in perimeters adjacent to roads.

Keywords: Durango, Mexico, geographically weighted regression, ordinary least squares, stationarity

Introduction

In Mexico, forest fires are strongly influenced by environmental, topographic, and socioeconomic factors (Fulé and Covington 1999; Rodriguez-Trejo and Fulé 2003). Environmental factors, such as precipitation and temperature, affect soil moisture and modify biomass production of trees, weeds, and grass, whose dry matter eventually serves as fuel. Typically, years of widespread fire coincide with dry, hot years that follow wet years in which biomass thrives (Drury and Veblen 2008). Fire behavior is also related to elevation, aspect, and farming activities (Rodriguez-Trejo and Fulé 2003). Forest fires are generally more common in south-exposed, hill-slope habitat types than in flat or north-exposed communities, which may be a result of variable micro-climate conditions (Drury and Veblen 2008).

Human activities are also an important factor that influences forest fire occurrence (Rodriguez-Trejo and Fulé 2003). Many farmers use fire as the main tool to purposely clear the land and grow basic crops such as corn and beans, or to promote the regrowth of grass. Escaped fires from agriculture or cattle grazing, which are no longer under human control, coupled with atypical environmental conditions, often result in the spreading of large, severe fires that not only destroy flora and fauna but also affect the general population directly (Rodriguez-Trejo and Fulé 2003). As a result, forest fires tend to occur more in areas close to towns and roads. When fire burns the same areas repeatedly, little accumulation of fuel occurs allowing the presence of small, low-intensity fires. However, when it is sporadic and occurs in large, scattered areas, there is a high chance to have moderate to severe fires that may replace the forest cover completely (Rodriguez-Trejo 2008).

Modeling fire size due to environmental, topographic, and human factors can be done through statistical methods (Wimberly et al. 2009). Conventional statistics, based on ordinary least squares (OLS), assumes that observations are independent and that the model parameters are valid for an area from which the data were sampled (Burt and Barber 1996). However, these assumptions do not entirely apply for factors with spatial differences and dependency. Ignoring these differences often lead to incorrect predictions of fire occurrence (Koutsias et al. 2010).

The similarity between neighbors and their high degree of dependence is supported by the first law of geography that states that everything is related with everything else, but closer things are more related (Tobler 1970). For example, two points: A and B, which share the same elevation, may have different precipitation patterns, but points closer to either one are more likely to

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have similar ones. In this case, a different way of regression modeling is necessary: one in which local similarities or spatial heterogeneity is accounted for and regression coefficients are assumed to be variable over space (Osborne et al. 2007).

Until now, no studies have been conducted to evaluate the relationship between fire and the spatial heterogeneity of explanatory variables in Mexico. Studies on this type of relationships have been done mainly in the United States (US) and other parts of the world. Tulbure et al. (2011) analyzed the spatial and temporal patterns of fire in agricultural landscapes of the central US. They found that the monthly total number of fire detections peaked in April and was higher in areas dominated by agriculture than areas dominated by forest. Poudyal et al. (2012) used geographically weighted regression to examine spatial variation in the association between social vulnerability and wildfire risk in six southern US states—Alabama, Arkansas, Florida, Georgia, Mississippi, and South Carolina. They identified geographical clusters where the social vulnerability varied positively with wildfire risk across all six states. Sá et al. (2011) evaluated fire incidence (expressed as the mean burned area) and various environmental and anthropogenic factors, such as precipitation, temperature, vegetation type, soil water, population, and agriculture in the sub-Saharan Africa. They found that vegetation had the most significant relationship with fire incidence and, overall, climate variables were more important than anthropogenic factors.

Modeling fire size and the spatial stationarity of the explanatory factors can aid forest fire managers in prioritizing fire-prone ecosystems for mitigation programming (Poudyal et al. 2012). Less humid areas, for example, will require more resources and must be placed at the top of the fire suppression agenda. Knowing the distinct effects of factors like precipitation, temperature, or elevation, among others, requires the application of modeling techniques that consider their spatial, complex heterogeneity. One of the main advantages of modeling the spatial heterogeneity is that not only we can construct maps to visualize spatial patterns but also we can apply statistical tests to check for significant differences of these patterns.

The overall objective of this study was to analyze the spatial heterogeneity of the factors influencing forest fire size, expressed as the number of hectares affected, in the state of Durango, Mexico. Factors included precipitation, temperature, elevation, slope, aspect, and distance to towns, roads, deforested areas, crops, and grasslands. The study used a spatial statistic method known as geographically weighted regression (GWR) (Fotheringham et al. 2002) to evaluate the factors. The study also analyzed whether localized model parameters were improved from OLS, and examined the spatial patterns of both model results.

Material and methods

Study area

The study was conducted in the western part of the state of Durango, Mexico, which hosts a variety of temperate forest species. Durango is the largest state with pine-oak forests in the country (Gonzalez-Elizondo et al. 2012), but one of the most affected by forest fires (CONAFOR 2012) (Fig. 1). The state is crossed from north to south by a mountain range known as the Sierra Madre Occidental, with elevations going from 1,300 to 3,300 m above sea level. Average temperature in this area ranges from 12 to 18 ºC and annual precipitation varies from 700 to 1200 mm.

The diversity in climate and topography accounts for the diversity of softwood-hardwood communities where *Pinus* spp and *Quercus* spp constitute the majority of trees (Gonzalez-Elizondo et al. 2012). Where the slope allows organic and mineral material build-up, soils are deep and mainly derived from igneous material, although metamorphic rocks are present in the west and northwest portions of the area (World Wildlife Fund 2006).

Steep-sloped mountains have shaped portions of the Sierra, though deep valleys, tall canyons, and cliffs also contour the Sierra Madre scenography. These steep-sided cliffs have thinner soils, limiting vegetation to chaparral types characterized by dense clumps of *Arctostaphylos pungens*, *Quercus potosinai,* and *Q. rugosa* (World Wildlife Fund 2006). There are also areas of natural pasture with *Muhlembergia* spp, *Aristida* spp., *Bouteloua* spp., and *Heteropogon* spp. (Gonzalez-Elizondo et al. 2012), which constitute the main fuel for frequent fires (Rodriguez-Trejo and Fulé 2003). Close to 80% of these forests are community owned (under the name of *ejidos*), where village members or *ejidatarios*, along with the government, are responsible for their forests' protection, management, and conservation (Perez-Verdin et al. 2009).

Non-stationarity and geographically weighted regression

One key difference between OLS and GWR is the assumption of stationarity. Stationarity refers to the tendency for any relationship to vary spatially (Fotheringham et al. 2002). OLS assumes that all spatial processes are stationary in which a stimulus (i.e., elevation) causes the same response (site productivity) in the entire study area. However, stationarity is not the rule in spatial processes. Forest sites have different levels of productivity as a function of elevation (Kimsey et al. 2008). The size of fires differs at two locations even though both have the same elevation. As Osborne et al. (2007, p. 314) pointed out, OLS models can "…mask the processes being studied because they give an average picture of the relationship between the predictor and the response factors." This average picture, erroneously accepted for non-stationary factors, has been used to conceive the OLS method as global or a constant-parameter model. A multivariate OLS model can be expressed as:

$$\ln FIRE = \beta_0 + \sum \beta_i (X) + \varepsilon_i \quad (1)$$

where ln$FIRE$ is the logarithm of fire size (Ha), X are the predictors (factors), β are model parameters of i predictor, and ε is the error term. The natural logarithm is used to increase model performance and avoid negative values.

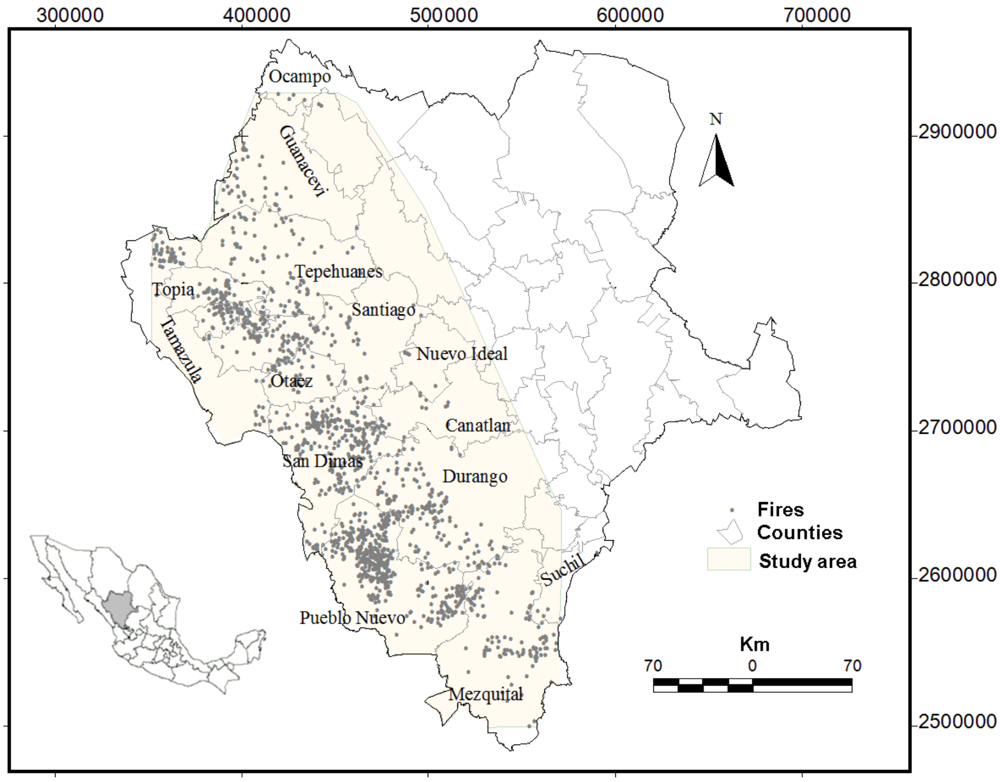

Fig. 1: Location of the study area, counties, and the forest fires occurred from 2000 to 2011 in Durango, Mexico (Map units are UTM coordinates).

In contrast, GWR models use the location of each observation and allow model parameters to vary as distance between points gets longer. At each data point (n), given by a set of coordinates (u, v), GWR fits a regression model by weighting all observations from that point as a function of distance. Thus, instead of having average model parameters, GWR produces non-constant model parameters, which eventually can be used to create maps and track spatial patterns (Fotheringham et al. 2002). Due to this localized form of prediction, GWR is known as local model.
The GWR model (Fotheringham et al. 2002) is expressed in the following form:

$$\ln FIRE(u,v)_n = \beta_0(u,v)_n + \sum_{i=1} \beta_1(u,v)_n X + \varepsilon(u,v)_n \tag{2}$$

where ($lnFIRE$)[1] is the response variable and stands for the logarithm of forest fire size (Ha) and (i) represents the set of predictors involving environmental, topographic, and human factors. Other terms have been identified before.

Since GWR weights the proximity of neighboring points (i.e., forest fires), it is necessary to identify an appropriate number of surrounding neighbors. This searching circle (or bandwidth, as is commonly called) depends on the distance between the points, the similarity of the area (distribution patterns), and the error occurring during the simulation. One of the most common methods to identify the bandwidth is through minimization of the Akaike Information Criterion (AIC) (Fotheringham et al. 2002). The AIC is a measure of the relative distance between the regression model to be fitted and the unknown true model. Thus, regression models with low AIC values indicate a closer approximation with the reality (Kupfer and Farris 2007).

The choices for minimization are either fixed (Gaussian) or adaptive (bi-square). In the former, the bandwidth needs to be specified in terms of the distance units used in the model. In the latter, the bandwidth is specified as the number of data points in the local sample used to estimate the parameters. Once the bandwidth (or circle search) has been defined, what follows is a fitting of the model that eventually produces the weights for each factor. In this case, closer points to the reference location receive a larger weight than those located farther away. The fitting can be assisted with common statistics such as the coefficient of determination, standard error, AIC, and residual analysis. Residuals can be spatially distributed as randomly, dispersed, or aggregated. It is desirable that residuals have a spatial random pattern to avoid concentration or high dispersion of errors (Wong and Lee 2005). The Moran's Index (Moran 1950) is used to test the hypothesis of spatial autocorrelation of residuals. The Moran's Index (Z)— one of the most common indices in the measurement of spatial autocorrelation—compares the value of a variable in a certain point to the value of the same variable in

[1] Wildfires are represented by points, not polygons (based on the official information). Every point includes information of the burned area and the time of fire containment, among other information. In this case, fire size is represented by the total affected area (Ha), and it is assumed that the point with such information is the center of the polygon.

another geographic point (Overmars et al. 2003). If the index approaches zero, then the variable is said to have a random distribution pattern (Wong and Lee 2005).

To test the null hypothesis of no stationarity of the factors, a Monte Carlo test is used to compare the observed variance of the estimated parameters of each of the factors against a data set of observed points taken at random (Hope 1968). Probability values are then estimated for each of the factors using an acceptable confidence level (usually set at 95%). Non-stationary parameter estimates can be spatially mapped using some interpolation techniques, such as the Kriging method, to evaluate the spatial patterns of the factors.

Sources of information and data processing

Fire information was obtained from the database of the National Forestry Commission (CONAFOR) for the period 2000-2011. This government-based agency coordinates operations for fire prevention and control and keeps a registry of all fire events occurred in the country along with latitude and longitude coordinates. The database includes, besides the location of wildfires, the size of fires (expressed in number of burned hectares), the number of days required to control the fire, vegetation affected, and the number of firefighters.

The independent variables (factors) were selected after reviewing literature on the fire regime variability in the area. Fulé and Covington (1999) evaluated elevation, slope gradients, and proximity to human habitation. Heyerdahl and Alvarado (2003) used slope gradient, aspect, and elevation. Drury and Veblen (2008) identified various climatic factors, vegetation types, land-use changes, and human influences as precursors of fire occurrence. Finally, Avila et al. (2010) used slope, temperature, precipitation, intensity of land-use change, and susceptibility of vegetation to fire. Our study extended the use of these factors—which were combined with distance to roads, distance to towns, and distance to other fire-prone areas, such as deforested areas, crops, and grassland areas—to a broader temporal and spatial scale.

A digital model showing elevation from the Instituto Nacional de Geografia (INEGI) was used to obtain information on elevation and aspect (INEGI 2012). Also, thematic maps from INEGI of vegetation types, roads, and population were used. Annual precipitation and mean temperature of the year in which the event took place were obtained from the database of the National Weather Service. Precipitation and temperature data were collected from the closest weather station to the fire. The variable that identifies types of property was obtained from the National Agrarian Registry (RAN 2012).

With the information gathered, it was possible to create new factors. For example, a population gravity index (*PGI*) was calculated as follows (Poudyal et al. 2011):

$$PGI = \sum_{k}^{K} \frac{P_k}{D_{ik}^2}, \forall_k : D \leq 20\text{km} \tag{3}$$

where P is the population of center k, K is the total number of towns, D is the distance (radius) between fire point n and town k, taken up to a 20 km radius of the fire. After evaluating several distances, the 20-km radius was specified because it ensured enough number of towns in the evaluation. The PGI captures the combined influence of population living nearby. High rates mean high human presence on fire events. Similarly, using geographic information system (GIS) tools, the closest distance between fires and population centers and roads were calculated. Table 1 shows the statistics of the factors used in the study.

Table 1: Descriptive statistics in the analysis of the factors that affect forest fire size in Durango, Mexico (Sample size = 1563).

Factor	Description	Mean	Stand. Dev.	Min.	Max.
SIZE	Affected area (Ha)	84.0	215.24	0	2600
PGI	Population Gravity Index	15.0	17.83	0	76
DISTROAD	Distance to roads (m)	1814	1870	0	13101
DISTOWN	Distance to towns (m)	3417	2228	10	11774
GRASSLAND	Distance to pasture areas (m)	2819	2329	0	9983
CROPS	Distance to crops (m)	3556	2750	0	9997
DEFOREST	Distance to deforested areas (m)	6257	5053	0	28569
PRECIP	Precipitation (mm)	607	191	174	1233
TEMP	Temperature (°C)	16.0	1.83	12	28
SLOPE	Slope (%)	11.5	9.6	0	52
ASPECT	Aspect (azimuth degrees)	178	108	0	360
ELEV	Elevation (msnm)	2437	301	753	3124

A computational package named GWR3.0®—developed by Martin Charlton, Stewart Fotheringham, and Chris Brunsdon—was used to fit both OLS and GWR models (Fotheringham et al. 2002) and eventually analyze spatial patterns of various environmental and socioeconomic factors driving fire size in Durango, Mexico. For the GWR, a Gaussian model where the bandwidth was automatically identified by adaptive iteration, was used (see details on GWR modeling in Fotheringham et al. 2002; Harris et al. 2011).

Both OLS and GWR results were converted to raster maps using the ordinary Kriging interpolation method of the ArcGIS® extension. Kriging is an advanced geostatistical procedure that generates an estimated surface from a scattered set of points with z-values (i.e., fire size). Unlike other interpolation methods supported by ArcGIS, Kriging involves an interactive search of the spatial behavior of a factor represented by the z-values before the best estimation method for generating the output surface is selected (ESRI 2012). Within Kriging, the spherical mathematical model was used to fit the semivariance of fire points.

Results

For the time period evaluated (2000–2011), 1,564 fires were recorded, which affected 136,370 hectares, giving an average of 87.2/ha/fire. Of this area, close to 44% were grasslands, 39% corresponded to herbaceous vegetation, and the rest were located in areas with trees and forest regeneration. To detect and contain

the fires, it took an average of 18.7 days per event. A test for spatial autocorrelation revealed that the geographic position of fires given by latitude (Z_{lat}) and longitude (Z_{long}) had an aggregated distribution pattern with a high concentration of fires near to roads and population centers (Z_{long}= 0.88, p <0.001; and Z_{lat} =0.74, p <0.001).

OLS model

Results of the OLS model indicated that all factors except the population gravity index (PGI) and aspect (ASPECT) were significant at a 0.05 probability value (Table 2). There was a positive relationship between the size of fires (expressed in number of burned hectares) and distance to roads (DISTROAD), distance to towns (DISTOWN), distance to grasslands (GRASSLAND), temperature (TEMP), SLOPE, and elevation (ELEV). But the relationship was negative with distance to crops (CROPS), distance to deforested areas (DEFOREST), and precipitation (PRECIP). The OLS model had an adjusted r^2 of 0.30 and the AIC was equal to 5566.

Table 2: Regression parameters of the OLS model for forest fires in Durango, Mexico

Factor	Estimate	Std Err	*t*-value	
Intercepted	-4.61432	1.86163	-2.479	*
PGI	-0.00390	0.00214	-1.821	
DISTROAD	0.00019	0.00002	8.637	*
DISTOWN	0.00024	0.00002	12.991	*
GRASSLAND	0.00005	0.00002	3.028	*
CROPS	-0.00004	0.00001	-2.737	*
DEFOREST	-0.00004	0.00001	-4.983	*
PRECIP	-0.00155	0.00020	-7.769	*
TEMP	0.29375	0.05953	4.935	*
SLOPE	0.01219	0.00420	2.900	*
ASPECT	-0.00055	0.00034	-1.640	
ELEV	0.00122	0.00037	3.295	*

* Significant at α≤0.05

Regression estimates indicated that distance to towns (DISTOWN) was the most important factor followed by distance to roads (DISTROAD), precipitation (PRECIP), distance to deforested areas (DEFOREST), and temperature (TEMP). Since regression estimates were constant through the study area, no maps were created to track the variability of the factors. The estimates were used only to visualize spatial patterns of the size of fires. Fig. 2 shows both OLS predicted and residual model results. According to the predicted model, the largest fires occur in the north and east while small to medium-sized fires are found in the west (Fig. 2a). This sort of geographic difference can be attributed to the division between windward and leeward orographic aspects. Windward is more humid, as it faces the Pacific Ocean, while leeward in the opposite side, is protected by the Sierra Madre, resulting in dryer conditions.

An analysis of residuals showed that there was a moderate concentration of errors, particularly of more than 100 ha, in the center of the state (Fig. 2b). The OLS residuals had a mean equal of 47.9 ha and were randomly distributed in the area (Moran Index, Z_{res}=0.025, p=0.859). A GWR analysis then proceeded to check whether errors could be reduced substantially.

GWR model

The GWR model had an adjusted r^2 of 45% and an AIC equal to 5330. The number of locations to fit the model was 1563 and the bandwidth size was defined at 336 neighbors. While both fixed and adaptive modes were applied, the latter gave better results (in terms of AIC, r^2, and residuals) and eventually was used in the analysis of spatial patterns of factors. Results indicated that the local model improved the AIC by 236 points, had 15% more in explained variation, and reduced the error by 11%. The F test also indicated that the reduction of the residual sum of squares between the global and local model was significant (p <0.05). These statistics suggest that the local model had better results compared to the global model (Table 3). The individual analysis of the medians of the parameters of the factors showed that the population gravity index (PGI), distance to crop areas (CROPS), precipitation (PRECIP), and aspect (ASPECT) were all negative. The rest of the parameters of the factors had positive values (Table 4).

Table 3: Analysis of variance for the OLS and GWR models of factors influencing forest fire size in Durango, Mexico

Source	Sum of Squares	Degrees of Freedom	Median Squares	*F*
Global model (OLS)	3169.4	12		
Local model (GWR)	867.8	120	7.24	
Residuals (GWR)	2301.6	1431	1.61	4.51*

* The F test is significant at α ≤0.05

The GWR model had a tendency to give high values of burned area from the north to the center of the state, but the GWR model showed fewer errors than the OLS model (Fig. 3). Analysis of frequencies showed that close to 77% of the GWR residuals had values of ±50 ha. This suggests that differences between observed and predicted values of the GWR model were mostly concentrated around zero and that the model is acceptable. The mean of residuals was equal to 37.7 ha and were randomly distributed in the area (Moran Index, Z_{res}= -0.029, p=0.845).

The Monte Carlo test revealed that the null hypothesis of stationarity of the factors: population gravity index (PGI), distance to roads (DISTROAD), distance to deforested areas (DEFOREST), precipitation (PRECIP), temperature (TEMP), and elevation (ELEV) is rejected (Table 4). The test suggests that these factors are significantly non-stationary in the study area. The spatial variation in the remaining factors was not significant, and in each case there was a high probability that the variation occurred by chance. The population gravity index (PGI) had negative estimates toward the south and positive estimates in the north center of the state (Fig. 4a). The effect of population is somewhat related to the road estimate results. Usually, roads are

constructed to connect towns and facilitate transportation of products. In the southeast area, characterized by a low road density and population, fire size increases as distance to roads increases (Fig. 4b). Other areas with high parameter values of distance to roads were found in the northeast part of the area.

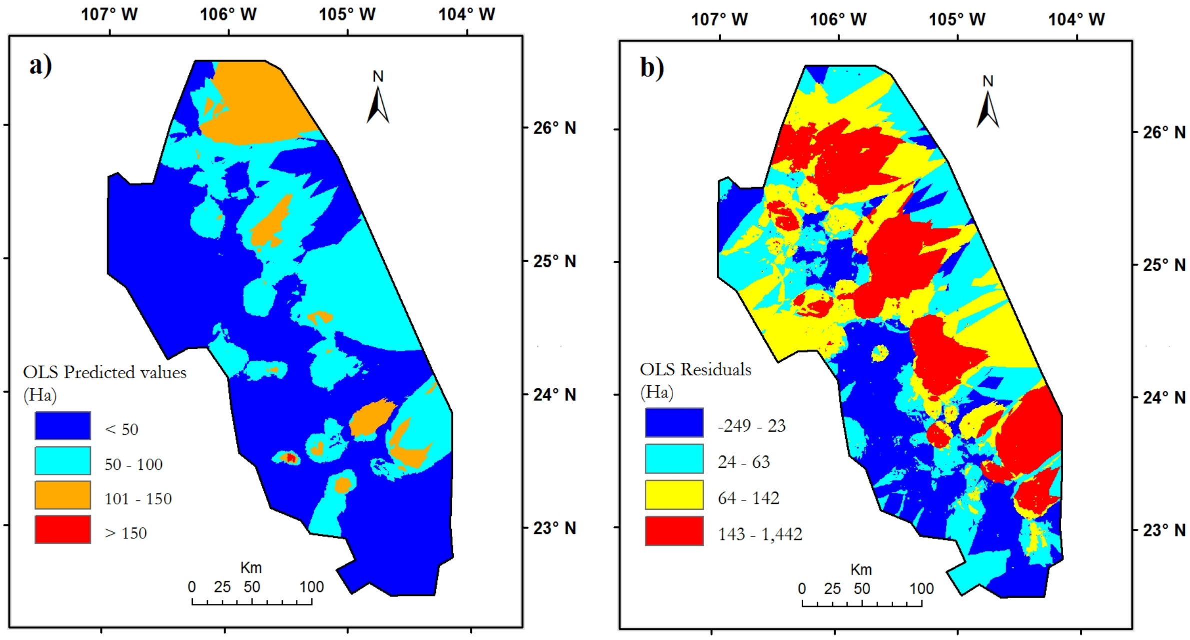

Fig. 2: Spatial analysis of derived forest fires estimates in Durango, Mexico. Fig. 2a) shows the results of the OLS predicted values, while 2b) shows the OLS residual model results

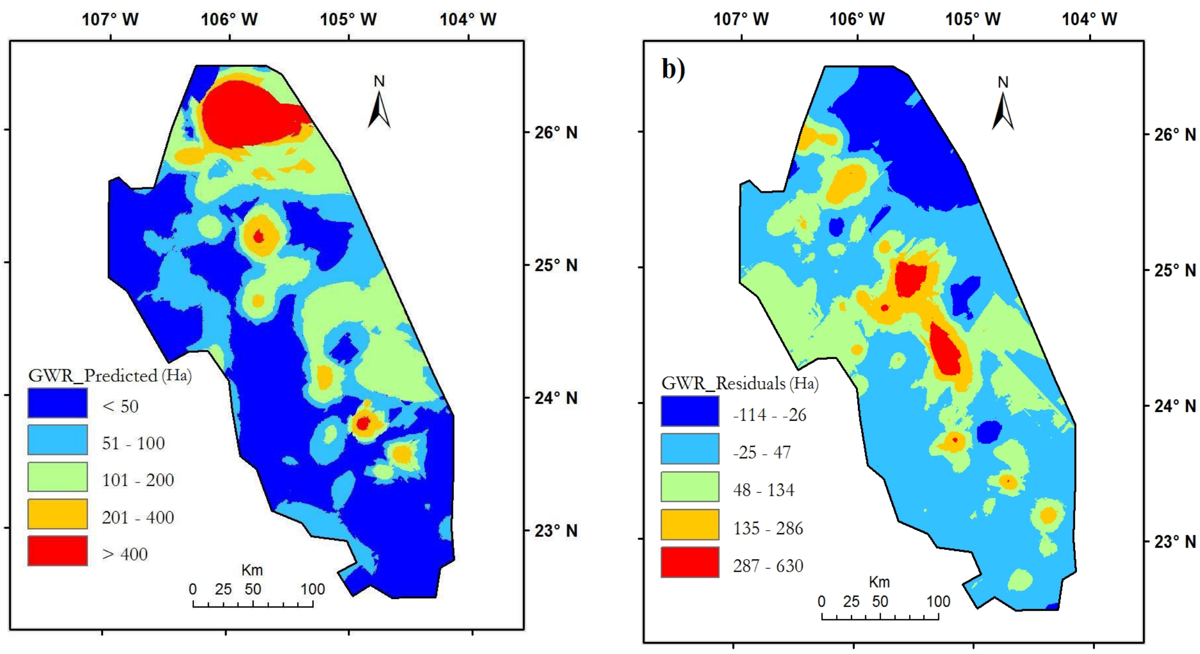

Fig. 3: Spatial analysis of derived forest fires estimates in Durango, Mexico. Fig. 3a) shows the results of the GWR predicted values, while 3b) shows the GWR residual model results.

Precipitation parameter estimates showed consistency in the entire study area. All parameter values had negative signs meaning that fire size increases as the area becomes dryer (Fig. 4c). Even though the parameters are all negative, it can be appreciated that the effect of precipitation on the size of fires is larger in the east than in the west. As expressed earlier, the western part of the state receives more humidity from the Pacific Ocean that reduces the possibility of large fires. Moreover, differences in precipitation also change the vegetation distribution patterns. The eastern foothills are characterized by extensive areas of natural

grass and herbs, oak and pine-oak woodlands, and chaparral (Gonzalez-Elizondo et al. 2012). As indicated by CONAFOR's fire records, these types of vegetation represent the majority of the affected area (83%).

Table 4: Ranges of the GWR parameter estimates and test of spatial variability of the factors influencing fire size in Durango, Mexico

Factor	Minimum	Lower quartile	Median	Upper quartile	Maximum	Monte Carlo test (*p*-value)
Intercepted	-17.09574	-8.12125	-2.09835	1.31895	15.88007	< 0.001 ***
PGI	-0.14620	-0.01591	-0.00042	0.01343	0.10388	< 0.001 ***
DISTROAD	-0.00009	0.00015	0.00023	0.00026	0.00034	0.02 *
DISTOWN	0.00008	0.00019	0.00023	0.00026	0.00036	0.43
GRASSLAND	-0.00018	-0.00003	0.00001	0.00004	0.00021	0.06
CROPS	-0.00012	-0.00004	-0.00002	0.00001	0.00009	0.52
DEFOREST	-0.00013	-0.00006	0.00003	0.00006	0.00016	< 0.001 ***
PRECIP	-0.00301	-0.00194	-0.00147	-0.00059	-0.00008	0.04 *
TEMP	-0.19785	0.10637	0.21046	0.41749	0.67269	0.01 **
SLOPE	-0.03527	-0.00318	0.00868	0.01423	0.02958	0.37
ASPECT	-0.00255	-0.00097	-0.00030	-0.00002	0.00077	0.90
ELEV	-0.00398	-0.00048	0.00078	0.00221	0.00364	< 0.001 ***

*** = Significant at 0.1%; ** = Significant at 1%; * = Significant at 5%.

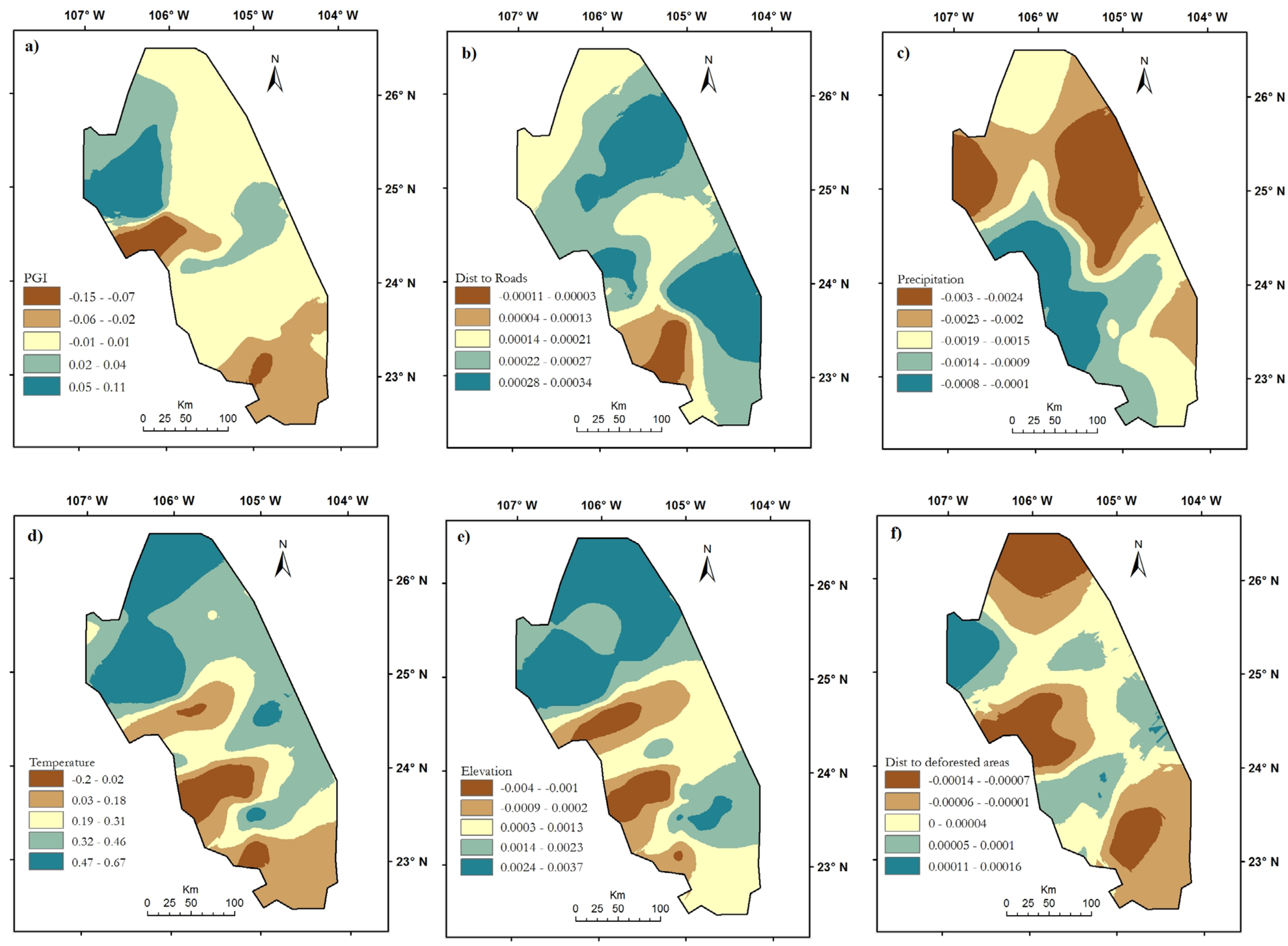

Fig. 4: Map distribution of GWR parameter estimates of the factors influencing forest fire size in Durango, Mexico: 4a) Population Gravity Index, 4b) Distance to Roads, 4c) Precipitation, 4d) Temperature, and 4e) Elevation.

Temperature had both positive and negative signs; the positive parameters were found in the north and east, while negative parameters were distributed from the center to the southwest (Fig. 4d). Again, it is convenient to mention that both precipitation and

temperature data were recorded in the year a fire took place. Drury and Veblen (2008) found a strong relationship between the precipitation and temperature in one year and the fires occurred the following year. In Mexico, most forest fires occur in the spring, meaning that the occurrence period extends until the vegetation, stimulated by the first rain, restart their period of growth and development. Thus, in this case, current precipitation is also strongly associated with fire size. Elevation showed high positive parameter values in the north and in the southeast, but negative signs in the west (Fig. 4e). The factor distance to deforested areas had negative effects in the north, center-east, and south. The parameters of this factor suggest that larger fires are more likely to occur in the northwest.

Discussion

According to the GWR model (Fig. 3a), there were various hot spots (areas with large fires) in the area clearly identified along an imaginary line that divides the leeward and windward orographic sides. These hot spots are generally found in roadless or low road density areas, namely the counties of Tepehuanes and Guanacevi, the east-central part of Santiago Papasquiaro, Otaez, and the north central part of Durango (see Fig. 1 for county location). Areas with small fires or “coldspots” were found around the population centers of El Salto and San Miguel de Cruces. It is important to mention that these coldspots were located in areas where forest landowners are heavily involved in forest resources management. The San Dimas and Pueblo Nuevo counties are characterized by a strong organization and cohesiveness, where landowners not only collaborate in fire containment, but also sponsor other forest restoration and management activities such as thinning, prescribed fire, and establishment of fire break lines. Though records indicate that there is a high frequency of fires in these areas, they are controlled more efficiently, that is, it takes less time to control a fire and fewer areas are affected.

The non-stationarity characteristic of population gravity index (PGI), distance to roads (DISTROAD), distance to deforested areas (DEFORESTED), precipitation (PRECIP), temperature (TEMP), and elevation (ELEV) suggests that fire size does not follow a constant pattern of variability and that it is influenced by the geographical position of fires. For example, fires that are geographically closer to roads have relatively less affected area than those at a greater distance. One reason for this relationship could be that fire suppression is difficult in remote areas and tends to affect more than those where road access is relatively easy. Similarly, two points may exhibit differences in the amount of affected area even though they have the same elevation, precipitation, and temperature. The spatial heterogeneity indicates that the geographic location determines the influence of a factor on the size of fires. These differences could not be detected by an OLS model in which it is assumed that factors had a constant effect over the entire study area.

As mentioned earlier, no studies have been conducted to evaluate the spatial heterogeneity of the factors influencing forest fire size in Mexico. Outside Mexico, one of the first studies analyzing the spatial heterogeneity of factors on fire incidence using GWR models was done in the sub-Saharan Africa (Sá et al., 2011). Here, the authors tested various environmental and anthropogenic factors and concluded that fire incidence is better described using GWR rather than OLS models, given the spatial variation of the regression coefficients. They also concluded that the occurrence of fire is primarily dependent on temperature and moisture. In our study, like the one in the sub-Saharan Africa, the GWR model performed better and showed the distinct spatial patterns of each independent factor. We believe, and agree with Sá et al. (2011), that the consideration of non-stationarity in fire modeling is important to better understand fire regimes and to more efficiently prioritize critical areas to fire occurrence.

The factors identified above as non-stationary (population gravity index, distance to roads, precipitation, temperature, and elevation) along with distance to towns were also the most important influences on fire size. One way to evaluate the individual performance of each factor is by analyzing the number of cases where it was statistically significant (Sá et al. 2011). Figure 5 shows the frequency of the *t*-test values of the coefficients of each factor resulting from the GWR model. For example, distance to roads had 1278 out of the 1563 cases (82%) with coefficients statistically significant (confidence level at 95%). Distance to towns had 1547 out of the 1563 cases (99%) with coefficients statistically significant. This indicates that the particular effect of this factor on fire size is significant in almost the entire area.

Precipitation and distance to deforested areas had 58% and 56% of statistically significant coefficients, respectively. Fig. 5 also shows that distance to towns and precipitation showed consistency in the signs; they remained unchanged at their minimum, median, and maximum values. The first was directly related whereas precipitation was inversely related to fire size. However, for the sake of space and practical visualization, the *t*-test values were mapped only for the factor distance to roads (Fig. 6).

These results confirmed that fire size is strongly influenced not only by environmental factors (precipitation, temperature, and elevation), but also by anthropogenic factors (population gravity index, distance to roads, and distance to towns). Little can be done to mitigate the effect of the former, but there is much to do to reduce the effect of the latter. While fires located near roads and towns are of low magnitude, their constant frequency increases the opportunity costs and decreases the possibility of attending other priorities. On the opposite side, fires occurring in remote, roadless areas are not that frequent. Yet, their effects are more catastrophic and dangerous to human beings. One of the most remembered events in southern Durango occurred in a natural protected, isolated area called “La Michilía”. Years of fire exclusion (Fulé and Covington 1999) and extreme dry conditions caused a big wildfire that burned down several hectares and killed one firefighter (Perez-Verdin et al., 2004).

To reduce the negative effect of both frequent, low-intensity and high-magnitude fires, Rodriguez-Trejo and Fulé (2003) discuss a number of measures that can be implemented to protect temperate forests. They cite, among other things, more training

for farmers, ranchers, and recreationists on the correct use of fire; regular maintenance of logging roads (including closure of roads); thinning and prescribed burnings; and fire breaks in perimeters adjacent to roads. Their management proposals are even divided in the cases when fires are excessive, normal, or insufficient.

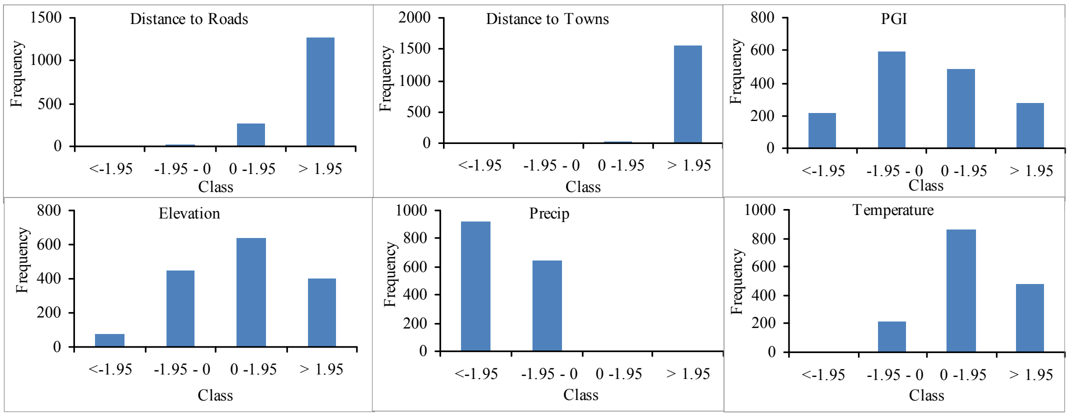

Fig. 5: GWR frequencies of *t* values for the factors influencing forest fire size in Durango, Mexico. The level of confidence was 95% (t = ± 1.96). See Table 1 for description of the factors.

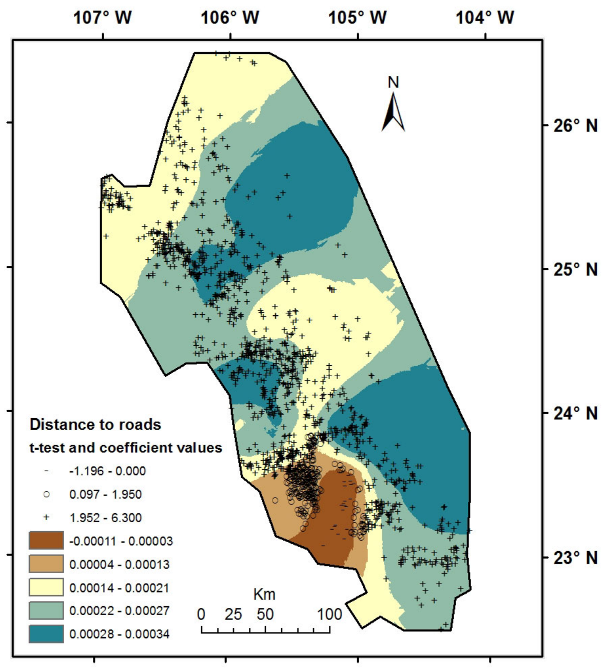

Fig. 6: *t*-test and coefficient values for the factor distance to roads in Durango, Mexico. The *t*-test values show the areas where the parameters are statistically significant (confidence level 95%). No significance is indicated by the signs “-” and “○”.

Finally, the improvement of the GWR model (r^2 =0.45), as compared to the OLS model (r^2 =0.30), was relatively low, though significant and otherwise acceptable. Reasons that explain the low performance of both models can be due to the lack of other important factors, such as fuel loadings. Fuel loading is one of the three basic elements (oxygen, heat, and fuel) that fires need to ignite. It is basically composed of forest residues, grass, and herbaceous vegetation. Its quantification can be done through direct measures in periodic forest inventories or after logging, or the effect of a meteorological event (snow, wind, or hurricanes). However, this measure was beyond this study; it requires long-term funding to constantly update the information. The inclusion of this factor may be essential in modeling fire size in the study area.

Conclusions

The geographically weighted regression (GWR) model is a very suitable tool for studying phenomena such as occurrence of forest fires. This model, unlike the simple linear regression method, assigns a different weight as the distance between points gets longer. It also helps to identify factors that have a non-constant effect according to the geographical position of points. In this study, factors such as the population gravity index, distance to roads and deforested areas, precipitation, temperature, and elevation were non-stationary. The GWR model revealed significant differences on fire size in the east and west of the study area. Larger fires were predicted in the north-east part than in the west, southwest of the study area. These differences can be attributed to the humidity coming from the Pacific Ocean that reduces the occurrence of large fires in the west.

The spatial heterogeneity of fire size is also influenced by population and road density. Less populated areas, which are typical of remote, roadless areas, have low impact on the size of fires. Spatial heterogeneity suggests that geographic location is a significant influence on the size of fires. These differences could not be detected by the OLS model in which it is assumed that factors had a constant effect over the entire study area. However, it should be emphasized that the GWR is to be used as complementary tool to OLS regression modeling and not as an alternative to it. The combined use of GWR and OLS models in studies analyzing stochastic variables is well recommended.

The most important factors affecting fire size can be classified as environmental (precipitation, temperature, and elevation) and

anthropogenic (distance to roads, distance to towns, and population gravity index). The focus of fire managers is on the factors that can be manipulated. Humans are the main cause of fires, but it is the man's resources that can reduce their magnitude. The results suggest the need for actions to promote awareness, raise the level of knowledge of stakeholders, and execute a series of measures to reduce the frequency of fires. These include more training for landowners who use fire for clearing and recreationists; maintenance of roads; application of thinning and prescribed burning, and fire breaks in perimeters adjacent to roads.

Our analysis of fire size was restricted by limitations in data availability. The role of other explanatory factors not analyzed here (e.g., fire loadings, soil humidity, etc.) would bring a more comprehensive understanding of the factors underlying fire occurrence patterns and their spatial relationships. The benefits associated with the design of better fire management policies with more refined information could easily overtake the costs required to get the information.

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